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(54) **PROCESS FOR AUTOMATICALLY MATCHING DATASETS**

FOREIGN PATENT DOCUMENTS

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EP 1211865 A2 6/2002  
EP 1706960 A1 10/2006  
(Continued)

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OTHER PUBLICATIONS

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Appaloosa Store, "String Similarity Algorithms Compared", Apr. 5, 2018, webpage downloaded on Oct. 20, 2020 from <https://medium.com/@appaloosastore/string-similarity-algorithms-compared-3f7b4d12f0ff>.

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(Continued)

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(51) **Int. Cl.**  
**G06Q 40/12** (2023.01)  
**G06Q 30/04** (2012.01)  
**G06F 16/2457** (2019.01)

(57) **ABSTRACT**

(52) **U.S. Cl.**  
CPC ..... **G06Q 40/12** (2013.12); **G06F 16/24578** (2019.01); **G06Q 30/04** (2013.01)

This document describes a non-transitory computer readable media programmed to enrich an entered record submitted to be matched with a dataset record stored on a data storage device. The enrichment is done by supplementing data in the entered record with customer data from a dataset. The media is further programmed to search through a plurality of dataset records in the dataset for the entered record. The search is programmed to first determine if the entered record unambiguously matches one of the dataset records or if the entered record unambiguously does not match one of the dataset records. If the entered record does not unambiguously match one of the dataset records, score match characteristics using a Fellegi-Sunter algorithm, save the score as a highest score if the score is above the highest score less a threshold, and save a location of one of the dataset records as a matching record if the score is above a previous highest score. Next, tune a Fellegi-Sunter algorithm parameter with the data from the entered record and data from one of the dataset records; and when the dataset records have been checked, return the matching record.

(58) **Field of Classification Search**  
None  
See application file for complete search history.

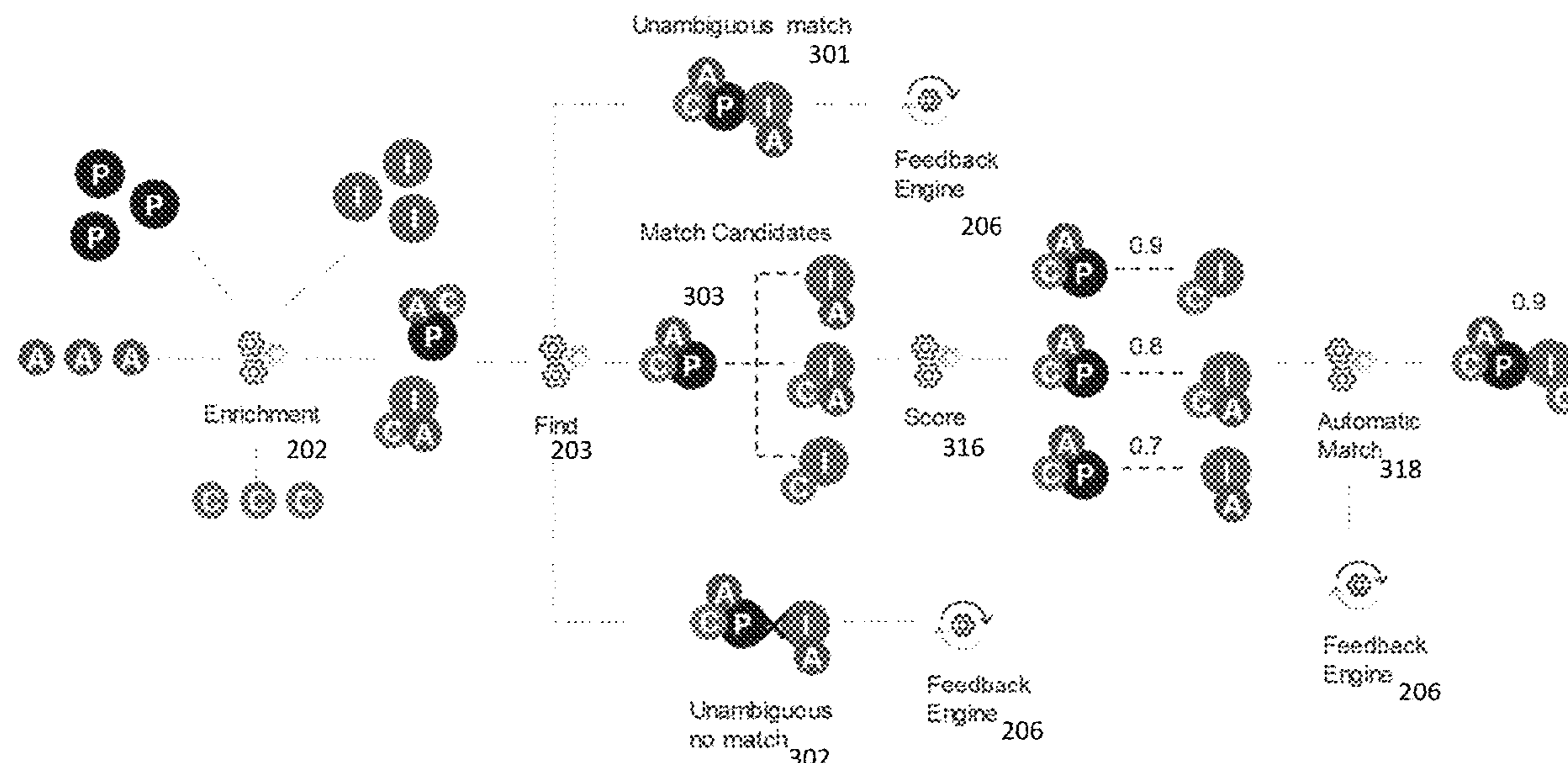
(56) **References Cited**

U.S. PATENT DOCUMENTS

4,575,793 A 3/1986 Morel et al.  
5,228,122 A 7/1993 Cahn et al.  
5,559,961 A 9/1996 Blonder  
5,600,735 A 2/1997 Seybold  
5,600,835 A 2/1997 Garland et al.  
5,634,008 A 5/1997 Gaffaney et al.

(Continued)

**20 Claims, 6 Drawing Sheets**



(56)

References Cited

U.S. PATENT DOCUMENTS

5,644,717 A	7/1997	Clark	10,523,681 B1	12/2019	Bulgakov et al.
5,790,798 A	8/1998	Beckett et al.	10,540,491 B1	1/2020	Martinez et al.
5,845,369 A	12/1998	Dunchock	10,552,837 B2	2/2020	Jia et al.
5,912,669 A	6/1999	Hsia	10,552,841 B1	2/2020	Dixit
5,961,592 A	10/1999	Hsia	10,586,220 B2	3/2020	Adams et al.
5,970,482 A	10/1999	Pham et al.	10,607,008 B2	3/2020	Byrne et al.
6,044,401 A	3/2000	Harvey	10,607,228 B1	3/2020	Gai et al.
6,192,411 B1	2/2001	Chan et al.	10,607,230 B2	3/2020	Adams et al.
6,195,452 B1	2/2001	Royer	10,621,587 B2	4/2020	Binns et al.
6,205,416 B1	3/2001	Butts et al.	10,699,075 B2	6/2020	Amend et al.
6,256,737 B1	7/2001	Bianco et al.	10,824,809 B2	11/2020	Kutsch et al.
6,523,016 B1	2/2003	Michalski	10,909,511 B2	2/2021	Chanyontpatanakul
6,651,099 B1	11/2003	Dietz et al.	10,929,851 B2	2/2021	Kang et al.
6,675,164 B2	1/2004	Kamath et al.	11,042,555 B1	6/2021	Kane et al.
6,687,693 B2	2/2004	Cereghini et al.	2002/0019945 A1	2/2002	Houston et al.
6,708,163 B1	3/2004	Kargupta et al.	2002/0056043 A1	5/2002	Glass
6,801,190 B1	10/2004	Robinson et al.	2002/0065938 A1	5/2002	Jungck et al.
6,845,369 B1	1/2005	Rodenburg	2002/0080123 A1	6/2002	Kennedy et al.
6,968,335 B2 *	11/2005	Bayliss ..... G06F 16/2471	2002/0099649 A1	7/2002	Lee et al.
7,044,365 B2	5/2006	Witherspoon	2002/0163934 A1	11/2002	Moore et al.
7,092,941 B1	8/2006	Campos	2003/0041042 A1	2/2003	Cohen et al.
7,174,462 B2	2/2007	Pering et al.	2003/0083764 A1	5/2003	Hong
7,308,436 B2	12/2007	Bala et al.	2003/0110394 A1	6/2003	Sharp et al.
7,415,509 B1	8/2008	Kaltenmark et al.	2003/0135612 A1	7/2003	Huntington et al.
7,584,128 B2	9/2009	Mason et al.	2003/0233305 A1	12/2003	Solomon
7,702,631 B1 *	4/2010	Basu ..... G06F 16/24556 707/999.006	2004/0034666 A1	2/2004	Chen
7,716,129 B1	5/2010	Tan et al.	2004/0186882 A1	9/2004	Ting
7,726,561 B2	6/2010	Katyal et al.	2004/0193512 A1	9/2004	Gobin et al.
7,729,959 B1	6/2010	Wells et al.	2005/0021650 A1	1/2005	Gusler et al.
7,730,521 B1	6/2010	Thesayi et al.	2005/0081158 A1	4/2005	Hwang
7,730,521 B1	6/2010	Thesayi et al.	2005/0154692 A1	7/2005	Jacobsen et al.
7,822,598 B2	10/2010	Carus et al.	2005/0177483 A1 *	8/2005	Napier ..... G06Q 40/00 705/35
7,831,703 B2	11/2010	Krelbaum et al.	2006/0101048 A1	5/2006	Mazzagatti et al.
7,860,783 B2	12/2010	Yang et al.	2006/0155751 A1	7/2006	Geshwind et al.
7,970,669 B1	6/2011	Santos	2006/0190310 A1	8/2006	Gudla et al.
7,992,202 B2	8/2011	Won et al.	2006/0212270 A1	9/2006	Shiu et al.
8,229,875 B2	7/2012	Roychowdhury	2007/0100749 A1	5/2007	Bachu et al.
8,229,876 B2	7/2012	Roychowdhury	2007/0277224 A1	11/2007	Osborn et al.
8,392,975 B1	3/2013	Raghunath	2008/0104007 A1	5/2008	Bala
8,401,867 B2	3/2013	Lagadec et al.	2009/0059793 A1	3/2009	Greenberg
8,429,745 B1	4/2013	Casaburi et al.	2009/0094677 A1	4/2009	Pietraszek et al.
8,433,791 B2	4/2013	Krelbaum et al.	2009/0140838 A1	6/2009	Newman et al.
8,484,168 B2 *	7/2013	Bayliss ..... G06F 16/35 707/688	2009/0174667 A1	7/2009	Kocienda et al.
8,515,862 B2	8/2013	Zhang et al.	2009/0201257 A1	8/2009	Saitoh et al.
8,538,124 B1	9/2013	Harpel et al.	2009/0202153 A1	8/2009	Cortopassi et al.
8,638,939 B1	1/2014	Casey et al.	2009/0282039 A1 *	11/2009	Diamond ..... H04L 9/3066
8,650,624 B2	2/2014	Griffin et al.	2009/0307176 A1	12/2009	Jeong et al.
8,776,213 B2	7/2014	McLaughlin et al.	2009/0313693 A1	12/2009	Rogers
8,844,059 B1	9/2014	Manmohan	2010/0066540 A1	3/2010	Theobald et al.
8,881,005 B2	11/2014	Al et al.	2010/0130181 A1	5/2010	Won
9,015,036 B2	4/2015	Karov et al.	2010/0169958 A1	7/2010	Werner et al.
9,189,505 B2 *	11/2015	Bayliss ..... G06F 16/24578	2010/0185615 A1	7/2010	Monga
9,449,346 B1	9/2016	Hockey et al.	2010/0225443 A1	9/2010	Bayram et al.
9,489,627 B2	11/2016	Bala	2011/0055907 A1	3/2011	Narasimhan et al.
9,529,678 B2	12/2016	Krelbaum et al.	2011/0070864 A1	3/2011	Karam et al.
9,537,848 B2	1/2017	McLaughlin et al.	2011/0082911 A1	4/2011	Agnoni et al.
9,595,023 B1	3/2017	Hockey et al.	2011/0145587 A1	6/2011	Park
9,607,103 B2	3/2017	Anderson	2011/0251951 A1	10/2011	Kolkowitz et al.
9,667,609 B2	5/2017	McLaughlin et al.	2011/0298753 A1	12/2011	Chuang et al.
9,691,085 B2	6/2017	Scheidelman	2012/0041683 A1	2/2012	Vaske et al.
9,798,984 B2	10/2017	Paleja et al.	2012/0124662 A1	5/2012	Baca et al.
9,811,650 B2	11/2017	Todeschini	2012/0127102 A1	5/2012	Uenohara et al.
10,037,533 B2	7/2018	Caldera	2012/0151553 A1	6/2012	Burgess et al.
10,152,680 B1	12/2018	Myrick et al.	2013/0071816 A1	3/2013	Singh et al.
10,235,356 B2	3/2019	Amend et al.	2013/0117246 A1	5/2013	Cabaniols et al.
10,242,258 B2	3/2019	Guo et al.	2013/0231974 A1	9/2013	Harris et al.
10,319,029 B1	6/2019	Hockey et al.	2013/0254115 A1	9/2013	Pasa et al.
10,320,800 B2	6/2019	Guo et al.	2013/0339141 A1	12/2013	Stibel et al.
10,402,817 B1	9/2019	Benkreira et al.	2014/0006347 A1	1/2014	Qureshi et al.
10,414,197 B2	9/2019	Jesurum	2014/0067656 A1	3/2014	Cohen et al.
10,440,015 B1	10/2019	Pham et al.	2014/0149130 A1	5/2014	Getchius
10,467,631 B2	11/2019	Dhurandhar et al.	2014/0366159 A1	12/2014	Cohen
10,510,083 B1	12/2019	Vukich et al.	2015/0039473 A1	2/2015	Hu et al.
10,511,605 B2	12/2019	Ramberg et al.	2015/0220509 A1	8/2015	Karov Zangvil et al.
			2015/0254308 A1 *	9/2015	Scott ..... G06F 16/23 707/780
			2015/0264573 A1	9/2015	Giordano et al.
			2015/0348041 A1	12/2015	Campbell et al.

(56)

References Cited

U.S. PATENT DOCUMENTS

2016/0041984 A1 2/2016 Kaneda et al.  
 2016/0352759 A1 12/2016 Zhai  
 2017/0039219 A1 2/2017 Acharya et al.  
 2017/0068954 A1 3/2017 Hockey et al.  
 2017/0070500 A1 3/2017 Hockey et al.  
 2017/0154382 A1 6/2017 McLaughlin et al.  
 2017/0163664 A1 6/2017 Nagalla et al.  
 2017/0177743 A1 6/2017 Bhattacharjee et al.  
 2017/0300911 A1 10/2017 Alnajem  
 2018/0107944 A1 4/2018 Lin et al.  
 2018/0349924 A1 12/2018 Shah et al.  
 2018/0357434 A1\* 12/2018 Roy ..... G06F 21/6209  
 2019/0014101 A1 1/2019 Hockey et al.  
 2019/0182233 A1 6/2019 Hockey et al.  
 2019/0197189 A1 6/2019 Studnicka  
 2019/0228411 A1 7/2019 Hernandez-Ellsworth et al.  
 2019/0318122 A1 10/2019 Hockey et al.  
 2019/0347281 A1 11/2019 Natterer  
 2019/0349371 A1 11/2019 Smith et al.  
 2019/0373001 A1 12/2019 Deeb et al.  
 2020/0019964 A1 1/2020 Miller et al.  
 2020/0117800 A1 4/2020 Ramberg et al.  
 2020/0279275 A1 9/2020 Kelly et al.  
 2021/0049326 A1 2/2021 Amend et al.  
 2021/0110447 A1 4/2021 Ransom et al.

FOREIGN PATENT DOCUMENTS

EP 2653982 A1 10/2013  
 EP 2636149 A4 10/2016  
 IL 176551 A 9/2012  
 IN 219405 3/2007  
 KR 10-0723738 B1 5/2007  
 TW 201723907 A 7/2017  
 WO 01/25914 A2 4/2001  
 WO 02/87124 A1 10/2002  
 WO 2002/100039 A2 12/2002  
 WO 03/73724 A2 9/2003  
 WO 2005/067209 A1 7/2005  
 WO 2012/061701 A1 5/2012  
 WO 2014/145395 A2 9/2014  
 WO 2015/175824 A1 11/2015  
 WO 2017/096206 A1 6/2017  
 WO 2017/209799 A1 12/2017  
 WO 2018/022157 A1 2/2018

OTHER PUBLICATIONS

Banon, Shay, "Geo Location and Search", elastic blog post, Aug. 16, 2010, webpage found at <https://www.elastic.co/blog/geo-location-and-search> on Oct. 15, 2019.  
 Bansal, Nikhil, Avrim Blum, and Shuchi Chawla. "Correlation clustering." *Machine Learning* 56.1-3 (2004): 89-113.  
 Bottomline Technologies (de), Inc, "4 Steps to Bringing a Positive ROI to Accounts Payable", 2019, a white paper downloaded from <https://go.bottomline.com/rs/498-XVR-738/images/4-Steps-Bringing-Positive-ROI-AP-IOFM-FDX-US-WTP-1802-088.pdf> on Sep. 30, 2019.  
 Bottomline Technologies, Bottomline Cyber Fraud & Risk Management:Secure Payments, marketing brochure.  
 Brasetvik, Alex, "Elasticsearch from the Bottom up, Part 1", Elastic, Sep. 16, 2013. Webpage found at <https://www.elastic.co/blog/found-elasticsearch-from-the-bottom-up> on Jun. 17, 2019.  
 Co-pending U.S. Appl. No. 13/135,507, filed Jul. 7, 2011.  
 Dalit Amitai, Shahar Cohen, Yulia Mayer, and Avital Seraty, "Fraud Detection Rule Optimization", U.S. Appl. No. 16/985,773, filed Aug. 5, 2020.  
 EMV Payment Tokenisation Specification, Technical Framework, EMVCo, LLC, Version 2.1, Jun. 2019.  
 EMV Payment Tokenisation, a Guide to Use Cases, EMVCo, LLC, Version 1.0, Jun. 2019.

Ephesoft, "KV Extraction Normalization", webpage downloaded from <https://ephesoft.com/docs/2019-1/moduleplugin-configuration/extraction-module/key-value-extraction-4040/key-value-extraction-plugin/kv-extraction-normalization/> on Oct. 1, 2019.  
 Experian, "Fuzzy address searching", webpage downloaded from <https://www.edq.com/glossary/fuzzy-address-searching/> on Oct. 8, 2019.  
 Fenz, Dustin, et al, "Efficient Similarity Search in Very Large String Sets", conference paper, Jun. 2012.  
 Finley, Thomas, and Thorsten Joachims. "Supervised clustering with support vector machines." *Proceedings of the 22nd international conference on Machine learning*, ACM, 2005.  
 G. Kou, Y. Peng, Y. Shi, M. Wise, W. Xu, Discovering credit cardholders behavior by multiple criteria linear programming, *Annals of Operations Research* 135, (2005) 261-274.  
 Haydn Shaughnessy, Solving the \$190 billion Annual Fraud Problem: More on Jumio, *Forbes*, Mar. 24, 2011.  
 Holl, Xavier and Andrew Chisholm, "Extracting structured data from invoices", *Proceedings of Australasian Language Technology Association Workshop*, 2018, pp. 53-59.  
 IdentityMing, Accelerated Fintech Compliance and Powerful Online Fraud Prevention Tools, website found at <https://identitymindglobal.com/momentum/> on Dec. 12, 2018.  
 International Search Report and Written Opinion received for PCT Patent Application No. PCT/IL05/000027, dated Jun. 2, 2005, 8 pages.  
 International Search Report and Written Opinion received for PCT Patent Application No. PCT/US17/13148, dated May 19, 2017, 11 pages.  
 Jeremy Olshan, How my bank tracked me to catch a thief, *MarketWatch*, Apr. 18, 2015.  
 Krawetz, N., "Looks Like It", 2011. Downloaded from <http://www.hackerfactor.com/blog/index.php?archives/432-Looks-Like-It.html> on May 27, 2020.  
 Lada, Dr. Maria, "Combined Search and Examination Report", UK Intellectual Property Office, May 18, 2020.  
 Meia et al., Comparing clusterings—an information based distance, *Journal of Multivariate Analysis* 98 (2007) 873-895.  
 Mitchell, Stuart, et al, "pulp Documentation", Release 1.4.6, Jan. 27, 2010.  
 Oracle(Registered) Warehouse Builder Data Modeling, ETL, and Data Quality Guide, Chapter 23, 11g Release 2 (11.2), Part No. E10935-04, Aug. 2011, web page downloaded from [https://docs.oracle.com/cd/E24693\\_01/owb.11203/e10935/match\\_merge.htm](https://docs.oracle.com/cd/E24693_01/owb.11203/e10935/match_merge.htm) on Apr. 16, 2020.  
 Postel et al.; "Telnet Protocol Specification" RFC 854; entered into the case on Apr. 18, 2013.  
 RodOn, "location extraction with fuzzy matching capabilities", Blog post on StackOverflow.com, Jul. 8, 2014, webpage downloaded from <https://stackoverflow.com/questions/24622693/location-extraction-with-fuzzy-matching-capabilities> on Oct. 8, 2019.  
 Rosette Text Analytics, "An Overview of Fuzzy Name Matching Techniques", Blog, Dec. 12, 2017, webpage downloaded from <https://www.rosette.com/blog/overview-fuzzy-name-matching-techniques/> on Oct. 15, 2019.  
 Samaneh Sorounejad, Zahra Zojaji, Reza Ebrahimi Atani, Amir Hassan Monadjemi, "A Survey of Credit Card Fraud Detection Techniques: Data and Technique Oriented Perspective", 2016.  
 Schulz, Klaus and Stoyan Mihov, "Fast String Correction with Levenshtein-Automata", *IJDAR* (2002) 5: 67. <https://doi.org/10.1007/s10032-002-0082-8>.  
 Segers, Jens, "Perceptual image hashes", Dec. 13, 2014, webpage downloaded from <https://jenssegers.com/perceptual-image-hashes> on Sep. 27, 2019.  
 Syphnt, "Unlock the value of your information", webpage downloaded from <https://www.syphnt.com/index.html> on Sep. 27, 2019.  
 The Telnet Protocol Microsoft Knowledgebase; entered into the case on Apr. 18, 2013.  
 Vogler, Raffael, "Comparison of String Distance Algorithms", Aug. 21, 2013, webpage downloaded on Oct. 20, 2020 from <https://www.joyofdala.de/blog/comparison-of-string-distance-algorithms>.  
 Wikil Kwak, Yong Shi, John J. Cheh, and Heeseok Lee, "Multiple Criteria Linear Programming Data Mining Approach: An Applica-

(56)

**References Cited**

## OTHER PUBLICATIONS

tion for Bankruptcy Prediction”, : Data Mining and Knowledge Management, Chinese Academy of Sciences Symposium, 2004, LNAI 3327, pp. 164-173, 2004.

Wikipedia, “Autoencoder”, web page downloaded from <http://en.wikipedia.org/wiki/Autoencoder> on Dec. 18, 2020.

Wikipedia, “Damerau-Levenshtein distance”, webpage downloaded on Oct. 20, 2020 from [https://en.wikipedia.org/wiki/Damerau-Levenshtein\\_distance](https://en.wikipedia.org/wiki/Damerau-Levenshtein_distance).

Wikipedia, “Reverse image search”, Sep. 12, 2019. Downloaded from: [https://en.wikipedia.org/w/index.php?title=Reverse\\_image\\_search&oldid=915372427](https://en.wikipedia.org/w/index.php?title=Reverse_image_search&oldid=915372427) on May 27, 2020.

Written Opinion of the International Searching authority for corresponding International Application No. PCT/US2016/064689 dated Feb. 22, 2017.

“Splink: Probabilistic record linkage and deduplication at scale”, Python Software Foundation, webpage downloaded from <https://pypi.org/project/splink/> on Jun. 1, 2021.

“Save time on monthly reconciliations with QuickBooks.”, Intuit Quickbooks, webpage downloaded from <https://quickbooks.intuit.com/accounting/bank-reconciliation/> on Jun. 1, 2021.

Sadinle, Mauricio, et al, “Approaches to Multiple Record Linkage”, ISI 2011 invited paper, 2011.

Winkler, William, et al, “An Application of the Fellegi-Sunter Model of Record Linkage to the 1990 U.S. Decennial Census”, US Census working paper No. RR91-09, 1991.

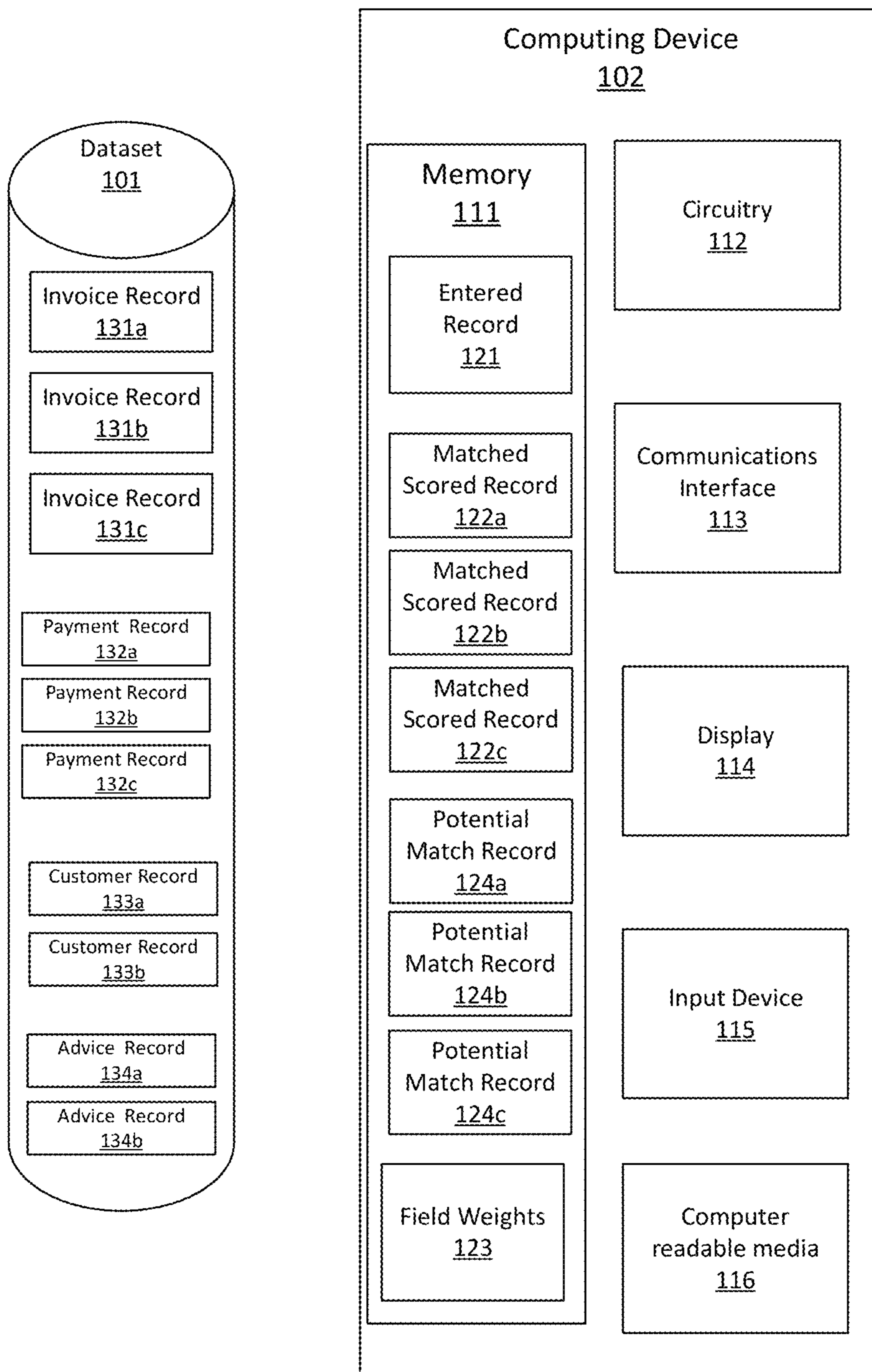
“Record Linkage”, Wikipedia, webpage downloaded on Jun. 3, 2021 from [https://en.wikipedia.org/wiki/Record\\_linkage](https://en.wikipedia.org/wiki/Record_linkage).

Fellegi, Ivan and Alan Sunter, “A Theory for Record Linkage”, Journal of the American Statistical Association, Dec. 1969, vol. 64, No. 328, pp. 1183-1210.

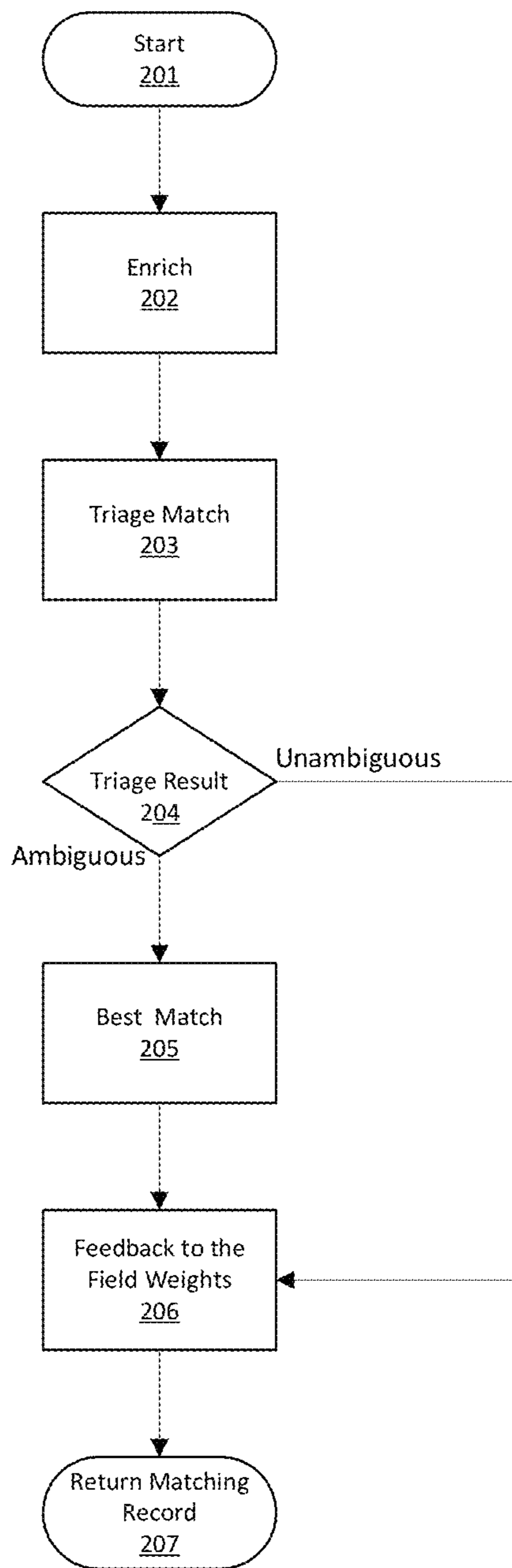
Enamorado, Ted, et al, “Using a Probabilistic Model to Assist Merging of Large-Scale Administrative Records”, American Political Science Review, 2019, vol. 113, No. 2, pp. 353-371.

Tiziana Tuoto, “Method: Fellegi-Sunter and Jaro Approach to Record Linkage”, a section in Memobust Handbook on Methodology of Modern Business Statistics, Mar. 26, 2014.

\* cited by examiner



*Figure 1*



*Figure 2*

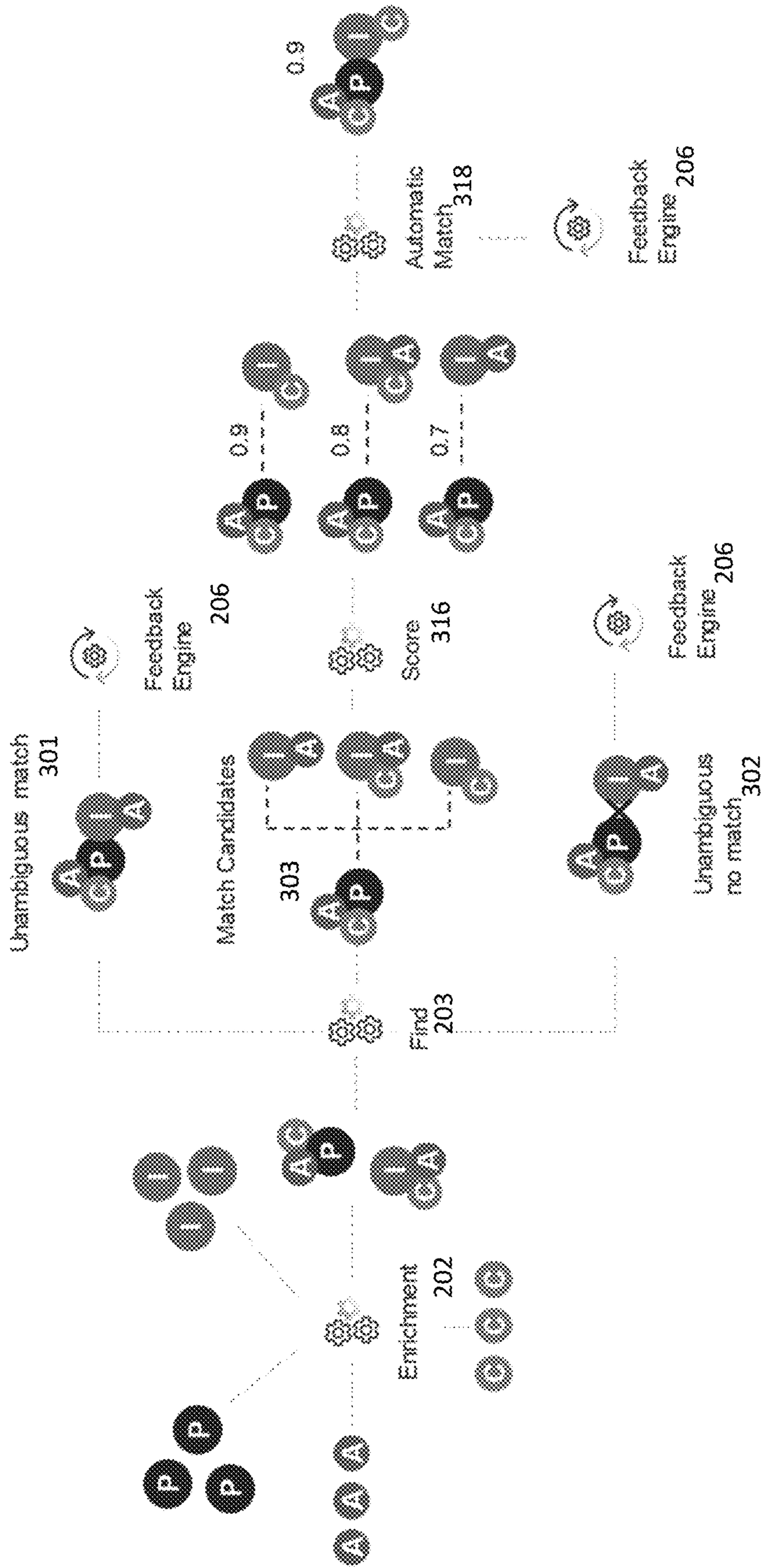
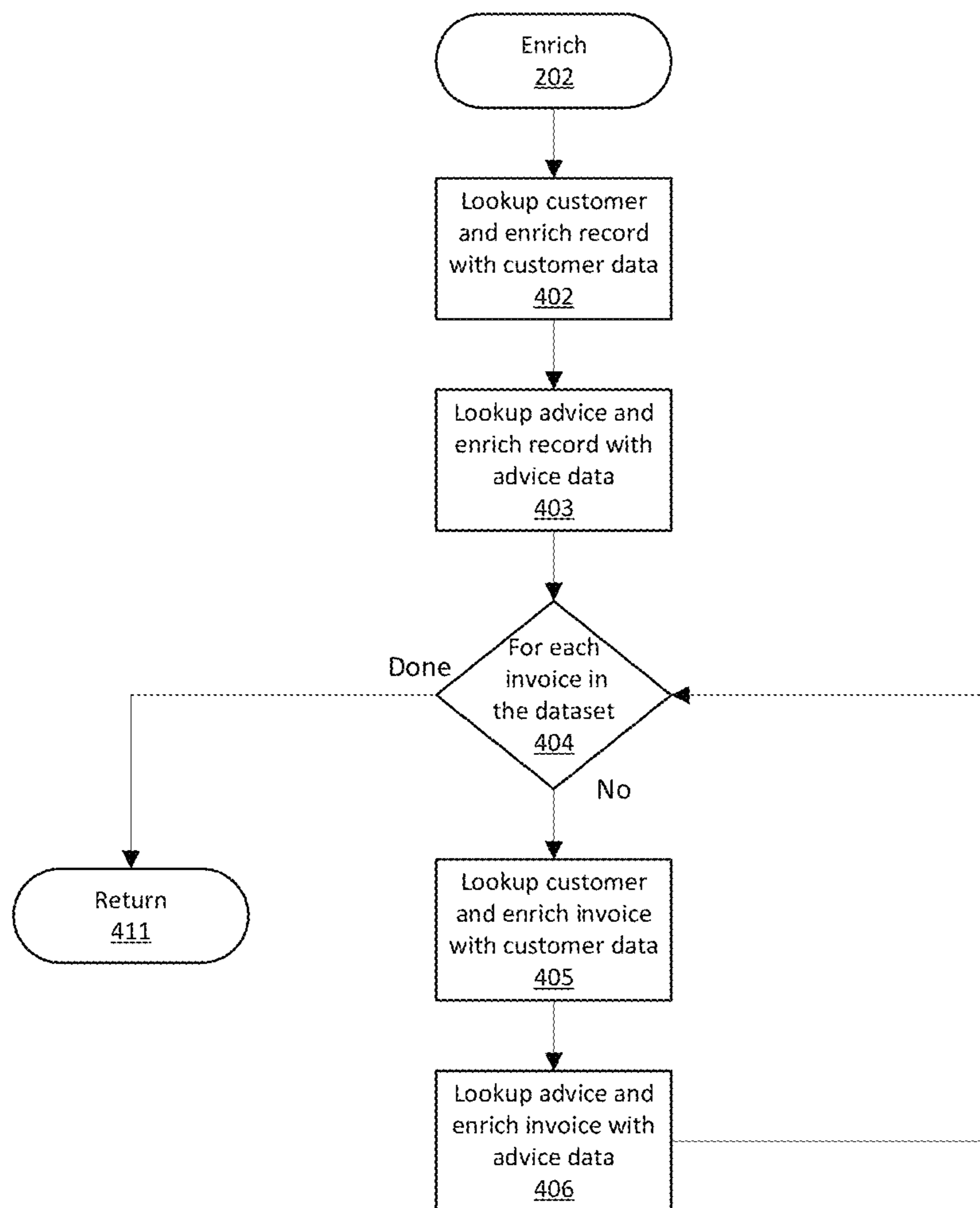
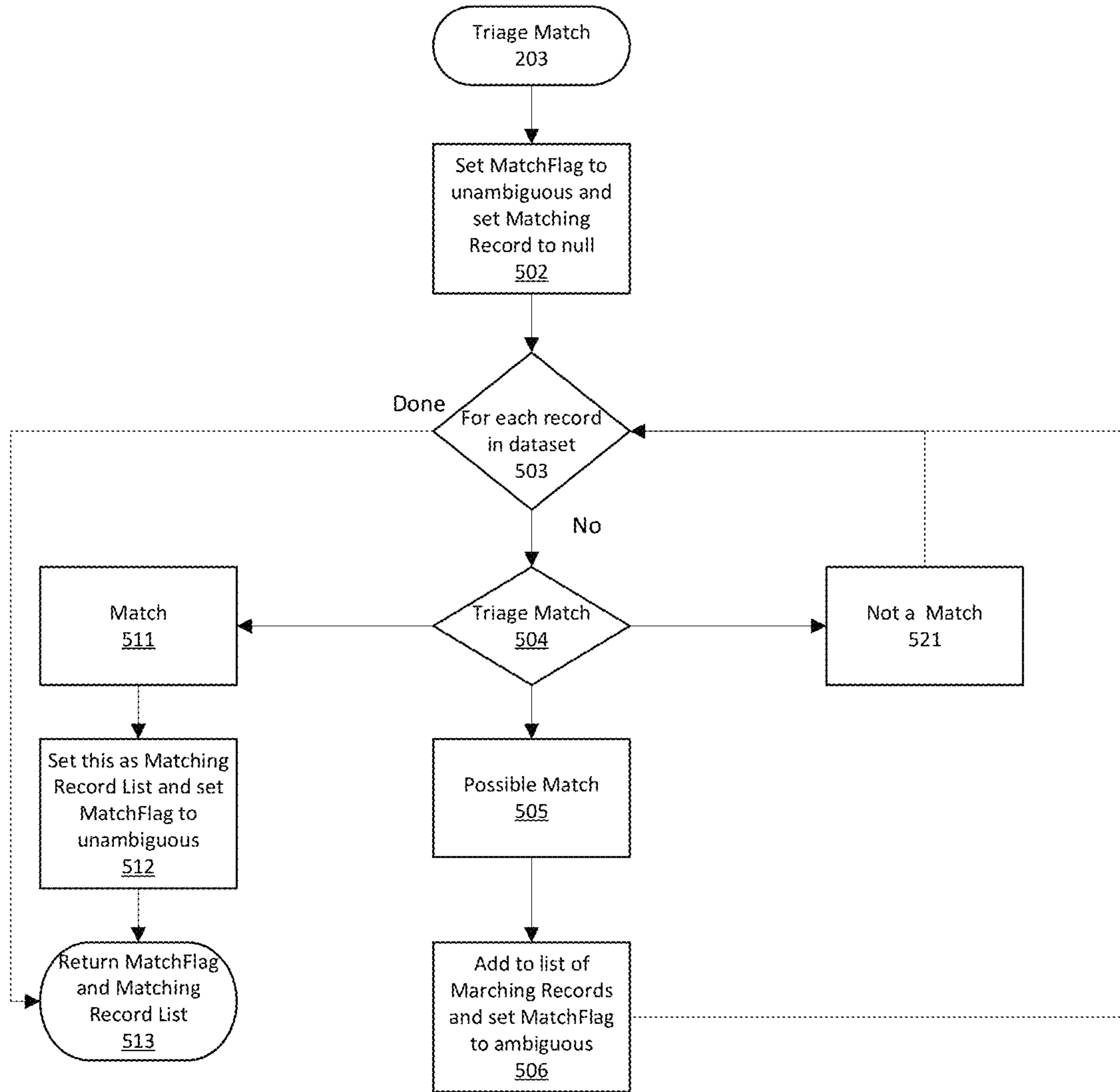


Figure 3

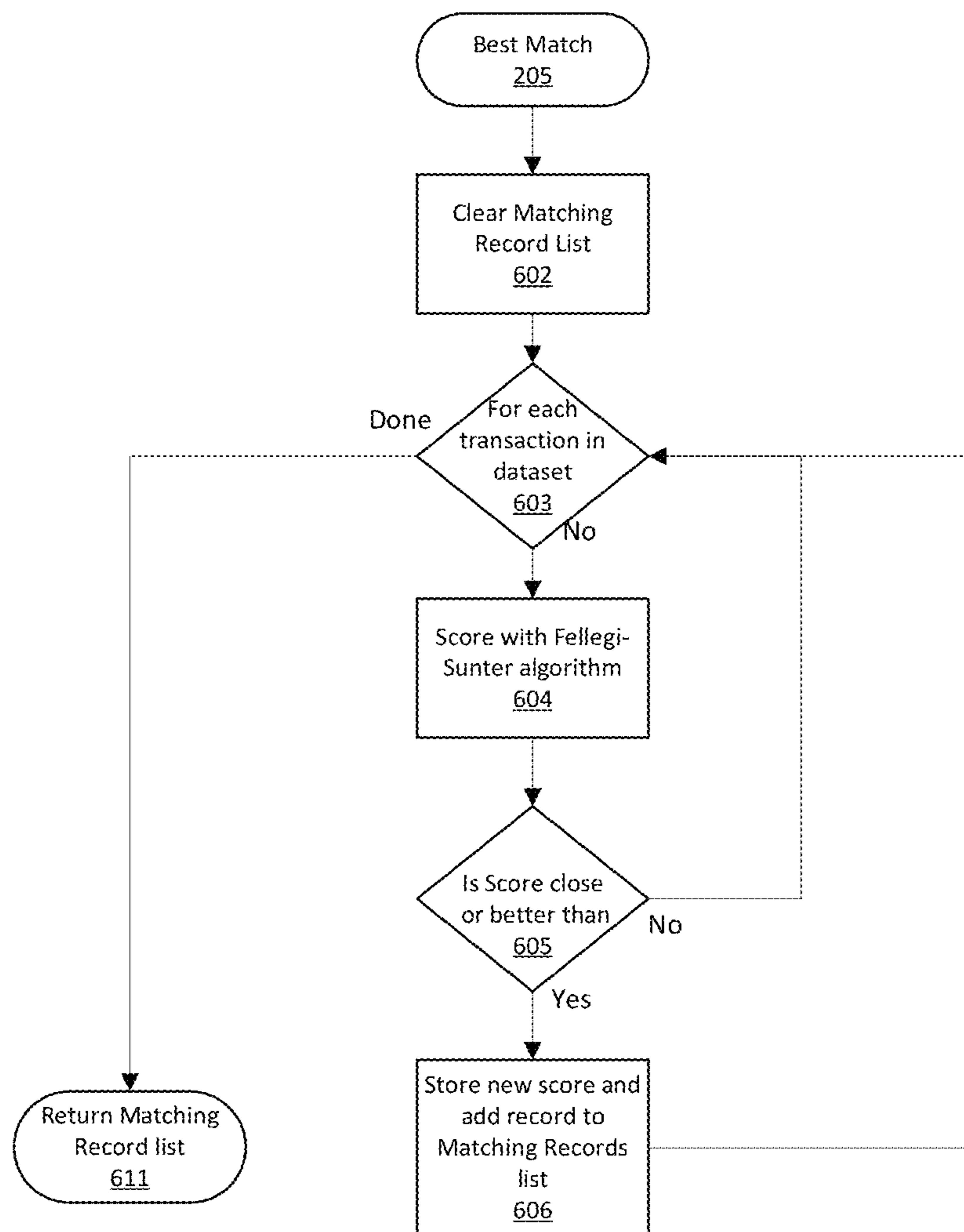


*Figure 4*





*Figure 5*



*Figure 6*

**1****PROCESS FOR AUTOMATICALLY  
MATCHING DATASETS****BACKGROUND****Prior Application**

This is a priority application.

**Technical Field**

The present disclosure relates generally to computer algorithms for matching records in a data set, specifically using data enrichment and triaging to optimize performance.

**Description of the Related Art**

There are many situations where a record needs to be found in a different dataset. An address read from an envelope needs to be matched to a postal database to determine the proper routing channels. Or in a network, a MAC address from a network packet needs to be found in a database to determine the physical location of the device that sent the message. In still another situation, a death record needs to be located in the roles of registered voters. In each case, the record may be formatted differently than in the dataset. The data in the record may be slightly different than the data in the dataset. Does the imperfect data match?

These questions also arise in the reconciliation of checks with banking records, or with payments received to open invoices or purchase orders to approved payments. There are numerous situations where the matching of imperfect data is required.

Current approaches to matching imperfect data are slow and inefficient, particularly with large datasets. The performance issue is particularly acute in scenarios where thousands of matches are needed in a day or hour. An improvement is needed. The apparatuses and methods described below articulate an optimized solution to the matching of imperfect data.

**SUMMARY OF THE INVENTIONS**

This document describes a non-transitory computer readable media programmed to enrich an entered record submitted to be matched with a dataset record stored on a data storage device. The enrichment is done by supplementing data in the entered record with customer data from a dataset. The media is further programmed to search through a plurality of dataset records in the dataset for the entered record. The search is programmed to first determine if the entered record unambiguously matches one of the dataset records or if the entered record unambiguously does not match one of the dataset records. If the entered record does not unambiguously match one of the dataset records, score match characteristics using a Fellegi-Sunter algorithm, save the score as a highest score if the score is above the highest score less a threshold, and save a location of one of the dataset records as a matching record if the score is above a previous highest score. Next, tune a Fellegi-Sunter algorithm parameter with the data from the entered record and data from one of the dataset records; and when the dataset records have been checked, return the matching record.

The dataset record could be a payment record and the media could be further programmed to enrich at least one payment record by supplementing data in at least one payment record with the customer data from the dataset. The

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dataset record could be an invoice record and the media could be further programmed to enrich at least one invoice record by supplementing data in at least one invoice record with the customer data from the dataset. The entered record could be related to a payment or an invoice. The threshold could be zero. The Fellegi-Sunter algorithm parameter could be a probability  $m$  that an amount field in the entered record matches an amount field in the dataset record. The Fellegi-Sunter algorithm parameter could be a probability  $n$  that a customer address field in the entered record does not match a customer address field in the dataset record.

A method is also described here. The method is made up of the steps of (1) enriching, with a computer, an entered record submitted to be matched with a dataset record on a data storage device by supplementing data in the entered record with customer data from a dataset, (2) searching through a plurality of dataset records in the dataset for the entered record, wherein the searching first determines if the entered record unambiguously matches one of the dataset records or if the entered record unambiguously does not match one of the dataset records, (3) if the entered record does not unambiguously match one of the dataset records, (3a) scoring match characteristics using a Fellegi-Sunter algorithm, (3b) saving the score as the highest score if the score is above the highest score, less a threshold, and (3c) saving a location of the one of the dataset records as a matching record if the score is above a previous highest score. The method continues by (4) tuning a Fellegi-Sunter algorithm parameter with the data from the entered record and data from one of the dataset records, and (5) when the dataset records have been checked, returning the matching record.

The dataset record could be a payment record and the method could also include (2a) enriching at least one payment record by supplementing data in at least one payment record with the customer data from the dataset. The dataset record could be an invoice record and the method could also include (2a) enriching at least one invoice record by supplementing data in at least one invoice record with the customer data from the dataset. The entered record could be related to a payment or an invoice. The threshold could be zero. The Fellegi-Sunter algorithm parameter could be a probability  $m$  that an amount field in the entered record matches an amount field in the dataset record. The Fellegi-Sunter algorithm parameter could be a probability  $n$  that a customer address field in the entered record does not match a customer address field in the dataset record.

**BRIEF DESCRIPTION OF THE DRAWINGS**

The annexed drawings, which are not necessarily to scale, show various aspects of the inventions in which similar reference numerals are used to indicate the same or similar parts in the various views.

FIG. 1 is one possible hardware implementation of the present inventions.

FIG. 2 is a flow chart of the steps to reconcile the record with the dataset.

FIG. 3 is a data flow view of the reconciliation process.

FIG. 4 is a flow chart of the enrichment process.

FIG. 5 is a flow chart of the triage matching process.

FIG. 6 is a flow chart of the best match process.

**DETAILED DESCRIPTION**

The present disclosure is now described in detail with reference to the drawings. In the drawings, each element

with a reference number is similar to other elements with the same reference number independent of any letter designation following the reference number. In the text, a reference number with a specific letter designation following the reference number refers to the specific element with the number and letter designation and a reference number without a specific letter designation refers to all elements with the same reference number independent of any letter designation following the reference number in the drawings.

The present disclosure provides several embodiments for matching records in a dataset where both the record and the dataset are made up of imperfect data. Many data applications rely on multiple data sources, merging data sets is an essential part of researchers' workflow. Unfortunately, a unique identifier that unambiguously links records is often unavailable, and data may contain missing and inaccurate information. These problems are severe especially when merging large-scale administrative records.

Starting with FIG. 1, a dataset **101** is located on a data storage device such as a disk drive, a RAID server, an optical drive, a memory device, a solid-state drive, or a similar device. The dataset **101** could be organized as a database, a set of files, a spreadsheet, a data structure, or similar. The dataset **101** includes a number of dataset records **131a-c**, **132a-c**, **133a-b**, **134a-b**. The dataset records **131a-c**, **132a-c**, **133a-b**, **134a-b** could be organized as a plurality of delimiter (comma, space, carriage return, etc) separated fields, fixed sized fields, free format text capable of being parsed into fields, or other data structures. These data records **131a-c**, **132a-c**, **133a-b**, **134a-b** contain the reference data that is being compared against. The data records **131a-c**, **132a-c**, **133a-b**, **134a-b** could be, but are not necessarily cleaned, and could contain misspelled words, a mix of spelled out and abbreviated words, nicknames and full names, missing fields, information in the wrong field, and other anomalies that prevent exact matches. The dataset **101** is not necessarily deduplicated.

In some embodiments, the dataset **101** contains a set of outstanding invoices I, **131a-c** representing all of the receivables for a company. The payments P, **132a-c** received by the company are also stored in the dataset **101**. The customer records C, **133a-b** for the company are also stored in the dataset **101**, as are the advice records A, **134a-b**. Some of these records are linked, perhaps using pointers in memory for example. When an invoice I, **131a-c** is entered, it may be linked to a customer account C, **133a-b**. Payments P, **132a-c** may contain advice information A, **134a-b**. With the match described herein, the payment P, **132a-c** is linked with an invoice I, **131a-c**.

The dataset **101** interfaces with a computing device **102**. This interface could be a direct bus connection, a local area network connection, an optical link, a wireless communications interface, or similar. The computing device **102** includes circuitry **112** such as a microprocessor and various interface and power circuitry. The computing device **102** also includes a communications interface **113** for interfacing the computing device **102** to networks such as the internet, local area networks, wireless networks, optical networks. The communications interface **113** could be a component of the interface with the dataset **101**. In some embodiments, the computing device **102** also includes a display **114** (such as an LED screen, a CRT monitor, a LED monitor, an LCD or laser projector, etc.) and/or an input device **115** (such as a keyboard, mouse, touchscreen, touchpad, check reader, license plate reader, credit card scanner, driver's license scanner, passport scanner, etc). The computing device **102** also includes or interfaces to computer readable media **116**.

The computing device includes memory **111** that connects to the circuitry **112**, the communications interface **113**, and perhaps to the display **114**, the computer readable media **116**, and the input device **115**. The memory **111** could include the computer readable media **116**.

The memory **111** contains the entered record **121** (a payment P or an invoice I) that is being searched for to match. It also includes the matched, scored records **122a-c** that hold the match score, potential matched records **124a-c**, and record (payment P or invoice I) in the dataset **101** for the records that appear to be a match. Further, the memory **111** includes the field weights **123** that are tuned parameters for calculating the score, such as m and u discussed below).

FIG. 2 is a flowchart of the algorithm for determining a match between a payment and an invoice that begins **201** with the entering of the record **121** (either a payment or an invoice) to find a match. Next, the record is enriched with existing data **202**. The stored payments and invoices are also enriched. The enrichment is described in FIG. 4.

Once the data is enriched, the data is triaged to see if a quick, unambiguous match between payment and invoice can be found **203**. This process is outlined in detail in FIG. 5.

If the triage result **204** is unambiguous then proceed to processing the feedback **206**.

If the triage result **204** is ambiguous, then additional processing is needed to identify the best match **205**. The best match **205** algorithm is shown in FIG. 6. Once the best match is identified, then feedback **206** is provided.

The feedback **206** adjusts the parameters used in the best match **205** algorithm. For instance, parameters u and m may be adjusted to tune the Fellegi-Sunter algorithm. Other parameters may be adjusted as well.

Once the feedback **206** algorithm has adjusted the parameters, the matching record could be returned **207** to the calling routine, if a matching record is found. If a match is not found, a null pointer may be returned in some embodiments. In other embodiments, a second parameter is returned indicating whether a match was found. In still other embodiments, a score indicating the confidence of the match is returned.

FIG. 3 shows a data flow through the system described herein. The enrichment process **202** takes invoice information I, payment information P, advice information A, and customer information C. The advice A is information about the data, such as an unstructured email response to a question about a payment. For example, a payment may arrive without any information, and an accounts receivable clerk may send an email asking about which invoice the payment is related to. The returned email may be one example of advice A.

The enrichment process **202** matches information from advice A and customers C with payments P or with invoices I to form enriched payments P,A,C or enriched invoices I,C,A. This combination is then sent through the find, or triage match **203** to see if a quick match can be made between the enriched payments P,A,C and an enriched invoice I,C,A (or any invoice I). The triage match **203** may also be run to match an enriched invoice I,C,A to a stored payment P (or an enriched payment P,A,C).

There are three possible results of the triage match **202**: the match could be unambiguous, with the invoice I (or enhanced invoice I,C,A) clearly matching the enriched payment P,A,C) **301**, or there could be an unambiguous mismatch **302**, or the match could be ambiguous **303**, with a plurality of match candidates.

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When there is an unambiguous match **301**, then the enriched invoice I,C,A (or the invoice itself I) is linked to the enriched payment P,A,C (or the payment P). The process is complete, the match is made. Once matched, the feedback engine **206** is run to update the parameters used in the scoring and fuzzy matching.

When there is an unambiguous mismatch **302**, then no link is made. The process is complete, the match is not made. No invoices I are found that match the payment P (or no payment P is found to match the invoice I). The feedback engine **206** is run to update the parameters used in the scoring and fuzzy matching.

When the match is ambiguous **303**, then each of the potential match candidate invoices I,A; I,C,A; I,C are scored **316** against the match with the payment P,A,C. Then the automatic match process **318** determines which match scored the highest, and the match between the invoice I and the payment P, and the link between the invoice I and the payment P is established. The feedback engine **206** is run to update the parameters used in the scoring and fuzzy matching.

FIG. 4 shows the details of the enrichment process **202**. This process begins by enhancing the information **402** in the entered record **121**. In one embodiment, the entered record has payment information P. If there is missing customer information in the entered record **121**, then the customer information C is looked up in the customer records **133a-b** in the dataset **101**. Any missing contact information from the customer record **133a-b** is copied into (enriched) **402** the entered record **121**. Any other missing information is filled in if it is easily accessible. In some embodiments, a search is done by customer name to find the customer record **133a-b**. In other embodiments, the customer number is used as an index to find the customer record **133a-b**.

If there is additional missing information in the entered record **121**, then the advice information A is looked up in the customer records **133a-b** in the dataset **101**. Any missing information from the advice record **134a-b** is copied into (enriched) **403** the entered record **121**. Any other missing information is filled in if it is easily accessible. The advice record **134a-b** could be found with a search or a lookup.

The enrichment process **202** then continues looking at every invoice in the dataset **404**. Each invoice **131a-c** is analyzed to see if it is missing customer information C. If so, then the invoice **131a-c** in the dataset **101** is enriched **405** by filling in missing data from customer data **133a-b**. In some embodiments, this enrichment is done by linking the invoice **131a-c** with the customer record **133a-b**. Each invoice **131a-c** is also analyzed to see if it is missing other information. If so, then the invoice **131a-c** in the dataset **101** is enriched **406** by filling in missing data from advice data **134a-b**. In some embodiments, this enrichment is done by linking the invoice **131a-c** with the advice record **134a-b**.

See Table 1 for an example of the parameters for an enrichment. The Property is the field of the invoice record **131a-c**, the identifier is the type of field, the disqualify is used by the triage match **203** to determine if the match of the field needs to be absolute or if it is optional. The unique check says whether the field is unique. And the ambiguous field determines if the match is unambiguous if the field matches.

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TABLE 1

Field	Identifier	Disqualify identifier if NO_MATCH	Unique check (for automatic match)	Unambiguous check (for automatic matching)
TransactionReference	Transaction	false	false	false
CustomerReference	Counter-Party	true	false	false
CustomerName	Counter-Party	true	false	false
InvoiceNumber	Invoice	true	false	true
CustomerName	Counter-Party	true	false	false
TransactionDate	Date	false	false	false
Amount	Amount	true	true	false
...	...	...	...	...

In some embodiments, the payment records **132a-c** are also enriched similarly.

Once all of the invoices **132a-c** have been enriched, the process ends and returns to the calling routine **411**.

In some embodiments, the enrichment **202** process continuously watches (as a background process) for new advice A and customers C and tries to link new information with payments P or invoices I in the system. Once a link is established between the new advice A or the new customer C, the properties in the invoices I or payments P are associated with the new advice A or new customer C populated automatically.

FIG. 5 shows the details of the triage match process **203**. A payment record **121** is passed to the triage match process **203**, with the goal to find a matching invoice I. This process also could be used to find payments P if the passed parameter **121** is an invoice. This process begins by initializing the variables for the search **502**. The MatchFlag is set to Unambiguous and the MatchingRecordList is set to null.

For each invoice **131a-c** in the dataset **101**, the incoming record **121** is checked against the next invoice **131a-c**. This triage match **504** is a simple comparison of the data in the two records. If it matches completely (in some embodiments, the match is not complete, but requires a match of certain fields, or alternatively, a match of a certain number of fields), then there is a complete match **511**. If none of the information matches (in some embodiments, the mismatch is not complete, but requires a mismatch of certain fields, or alternatively, a mismatch of a certain number of fields), then there is no match **521**. If some of the information matches, then there is a possible match **505**. In some embodiments, the possible match **505** is determined if there is neither a match **511** nor a not a match **521**, then a possible match **505** is determined for all other cases.

If there is no match **521**, the loop checks the next **503** invoice in the dataset **101**.

If there is a possible match **505**, then the invoice **131a-c** from the dataset **101** is added **506** to the list of possible matches **124a-c**. The MatchFlag is set to ambiguous. And then the invoice **131a-c** in the list is checked **503**.

If there is a match **511**, then the MatchFlag is set to unambiguous **512**, as we found the matching invoice I, and the invoice **132a-c** is copied to the head of the linked list of potentially matched records **124a**. This copying is done to clear the list of matches and replace it with the one matched record **124a**. The loop checking all records in the list is terminated, and the routine returns **513** the Match Flag and the list of potential matching records **124a**.

Once the entire list of invoices **131a-c** is checked **503**, the MatchFlag and the list of potential matching records **124a-c** are returned **513**.

Looking to FIG. 6, the detailed process of identifying the best match **205** is shown. The best match process **205** takes the entered record **121** and a list of potential matches **124a-c** as parameters and attempts to find the best match by scoring each match using the Fellegi-Sunter algorithm. The Fellegi-Sunter algorithm is described in “A Theory for Record Linkage” by Ivan P. Fellegi and Alan B. Sunter (*Journal of the American Statistical Association*, American Statistical Association, December 1969, Vol. 64, No. 328, pp. 1183-1210), incorporated herein by reference. The best scoring record **122a-c** is returned. In some embodiments, additional matches within a threshold distance to the best score are also returned.

The best match process **205** may start by clearing the matching record list **602**, initializing this list, and setting the BestScore value to 0. Next, the list of potential matches **124a-c** are processed one record by one **603**, first scoring the match between the potential match record with the entered record **121**. In some embodiments, the entered record **121** is a payment P, and the potential match list **124a-c** is a list of invoices I. In another embodiment, the entered record **121** is an invoice I, and the potential match list **124a-c** is a list of payments P.

In one embodiment, the match is scored with the Fellegi-Sunter algorithm **604**. The score is compared with the BestScore **605**, and if the score is better than the BestScore, then the BestScore is assigned the value of the score **606**. And the matching record from **124a-c** is saved in the matched scored record list **122a-c**. The score is within a threshold of the BestScore, then the matching record from **124a-c** is saved in the matched scored record list **122a-c** but the BestScore is not changed. Then the next record in the potential match list **124a-c** is checked. Once all of the records in the potential match list **124a-c** have been checked, the matched scored record list **122a-c** is returned to the calling routine **611**. In some embodiments, only the best scoring record is returned, and no threshold analysis is performed.

The best match process is called when there is a possible match **303**, **505**. Some of the fields may match but others may be missing or misspelled. The match is scored **216** to see how close the record **131a**, **131b**, **131c** in the dataset **101** matches incoming record **121**.

The Fellegi-Sunter algorithm compares the similarity of two records. This comparison is done on a field by field basis (aka level by level), calculating the probability that the field matches and a probability that the field does not match. The probabilities are then summed to determine a match score.

Fellegi and Sunter algorithm considers the binary comparison vector

$$\gamma_k = \begin{cases} 1 & \text{if } X_k^A = X_k^B \\ 0 & \text{otherwise} \end{cases}$$

For an observed comparison vector  $\gamma$ , the space of all comparison vectors,  $m(\gamma)$  is defined to be the conditional probability of observing  $\gamma$  given that the record pair is a true match: in formula  $m(\gamma) = P((a, b) \in M)$ . Similarly,  $u(\gamma) = P((a, b) \in U)$  denotes the conditional probability of observing  $\gamma$  given that the record pair is a true non-match.

There are two kinds of possible misclassification errors: false matches and false non-matches. The probability of false matches is:

$$\mu = P(M^*|M) = \sum u(\gamma)P(M^*|\gamma)$$

and the probability of a false non-match is:

$$\lambda = P(U^*|M) = \sum m(\gamma)P(U^*|\gamma)$$

The Fellegi-Sunter scoring uses the Bayes theorem to calculate a probability that the records match. For instance, the probability that we have found a true match, given that we observed this particular level (e.g. probability of true match given that emails matched exactly), is calculated. Observed patterns can be used to generate a probability of if a new record comparison is a true match or not.

For the purpose of initializing the scoring algorithm, we define the types of matches for a level (Entity name in this example):

TABLE 2

Type of match	Entity name (invoice)	Entity name (payment)
Different	Emerald Bank	Ruby Inc
Similar	Emerald Bank	Emerald Inc
Exact	Emerald Bank	Emerald Bank

These different fields are referred to as levels. A user can use as many levels as they want and can define. The algorithm discovers which rules (levels) are most important for distinguishing between possible matches and non-matches. Rule (level) importance is quantified by the m/u ratio, where a higher m/u ratio means that rule is more important for determining if a comparison is a true match.

The Bayes theorem is:

$$P(\text{True Match} | \text{Level}) = \frac{m_{kl} * \lambda}{m_{kl} * \lambda + u_{kl} * (1 - \lambda)}$$

Where  $\gamma$  indicates the value of the comparison, the index k designates the comparison column, and l designates the observed comparison level.  $P(\text{TrueMatch} | \text{Level})$  is the estimated prior probability that any comparison between a pair of records is a match. For instance, it is the probability that the cell at the column and level is a true match.

At the core of this estimation are the m and u probabilities (m and u are part of the field weights **123**). Here, m is the fraction of true matches for a given level and u is the fraction of non-matches for a given level. For instance, the m probability for level 2 (where emails exactly match) is the fraction of true matches having identical emails in both the invoice and payment tables.

If the level is a high similarity comparison (e.g. Emails match exactly), we expect a high m probability, because we would expect true matches to almost always have the same email (except for typos or missing entries). The u probability represents the chance that a non-match has a high similarity level in that column. (e.g. two different people share the same email by pure chance). We would expect First Name to have a higher u probability than Social Security Number, since there is more chance of two people sharing the same first name than social security number.

In reality, we don't have any knowledge of which records are true matches when we start the matching process. This means we don't know m or u and can't make any predictions. So, we begin with an educated guess (e.g. m=0.9,

u=0.2 for a level) and use the expectation maximization algorithm (based on the feedback 206) to converge on values of m and u which best fit the patterns in the data. It is also possible to use domain knowledge to set initial values of m and u.

The expectation maximization algorithm begins by estimating m, u (or manually choose these) for each column and level. Next, it computes the probability that each record comparison is a match/non-match (using Bayes Theorem). Then, the expectation maximization algorithm uses these probabilities to assign all the comparisons to predicted match/non-match. Next, the algorithm uses these predicted matches to calculate a new m, u. Finally, the algorithm iterates until m and u converge. As a result, we have a model which knows how each level of comparison influences the probability of a record being a match or a non-match.

It should be appreciated that many of the elements discussed in this specification may be implemented in a hardware circuit(s), a circuitry executing software code or instructions which are encoded within computer readable media accessible to the circuitry, or a combination of a hardware circuit(s) and a circuitry or control block of an integrated circuit executing machine readable code encoded within a computer readable media. As such, the term circuit, module, server, application, or other equivalent description of an element as used throughout this specification is, unless otherwise indicated, intended to encompass a hardware circuit (whether discrete elements or an integrated circuit block), a circuitry or control block executing code encoded in a computer readable media, or a combination of a hardware circuit(s) and a circuitry and/or control block executing such code.

All ranges and ratio limits disclosed in the specification and claims may be combined in any manner. Unless specifically stated otherwise, references to “a,” “an,” and/or “the” may include one or more than one, and that reference to an item in the singular may also include the item in the plural.

Although the inventions have been shown and described with respect to a certain embodiment or embodiments, equivalent alterations and modifications will occur to others skilled in the art upon the reading and understanding of this specification and the annexed drawings. In particular regard to the various functions performed by the above described elements (components, assemblies, devices, compositions, etc.), the terms (including a reference to a “means”) used to describe such elements are intended to correspond, unless otherwise indicated, to any element which performs the specified function of the described element (i.e., that is functionally equivalent), even though not structurally equivalent to the disclosed structure which performs the function in the herein illustrated exemplary embodiment or embodiments of the inventions. In addition, while a particular feature of the inventions may have been described above with respect to only one or more of several illustrated embodiments, such feature may be combined with one or more other features of the other embodiments, as may be desired and advantageous for any given or particular application.

The invention claimed is:

1. A non-transitory computer readable media programmed to:

enrich an entered record submitted to be matched with a dataset record stored on a data storage device by supplementing data in the entered record with customer data from a dataset;

search through a plurality of dataset records in the dataset for the entered record, wherein the search is programmed to first determine if the entered record unambiguously matches one of the dataset records or if the entered record unambiguously does not match the one of the dataset records;

determine if the entered record does not unambiguously match the one of the dataset records;

score match characteristics using a Fellegi-Sunter algorithm;

save the score as a highest score if the score is above the highest score less a threshold;

save a location of the one of the dataset records as a matching record if the score is above a previous highest score;

tune a Fellegi-Sunter algorithm parameter with the data from the entered record and data from the one of the dataset records; and

when the dataset records have been checked, return the matching record.

2. The non-transitory computer readable media of claim 1 wherein the dataset record is a payment record.

3. The non-transitory computer readable media of claim 2 further programmed to enrich at least one payment record by supplementing data in the at least one payment record with the customer data from the dataset.

4. The non-transitory computer readable media of claim 1 wherein the dataset record is an invoice record.

5. The non-transitory computer readable media of claim 4 further programmed to enrich at least one invoice record by supplementing data in the at least one invoice record with the customer data from the dataset.

6. The non-transitory computer readable media of claim 1 wherein the entered record is related to a payment.

7. The non-transitory computer readable media of claim 1 wherein the entered record is related to an invoice.

8. The non-transitory computer readable media of claim 1 wherein the threshold is zero.

9. The non-transitory computer readable media of claim 1 wherein the Fellegi-Sunter algorithm parameter is a probability m that an amount field in the entered record matches an amount field in the dataset record.

10. The non-transitory computer readable media of claim 1 wherein the Fellegi-Sunter algorithm parameter is a probability n that a customer address field in the entered record does not match a customer address field in the dataset record.

11. A method comprising:

enriching, with a computer, an entered record submitted to be matched with a dataset record on a data storage device by supplementing data in the entered record with customer data from a dataset;

searching through a plurality of dataset records in the dataset for the entered record, wherein the searching first determines if the entered record unambiguously matches one of the dataset records or if the entered record unambiguously does not match the one of the dataset records;

determining if the entered record does not unambiguously match the one of the dataset records;

scoring match characteristics using a Fellegi-Sunter algorithm;

saving the score as a highest score if the score is above the highest score, less a threshold;

saving a location of the one of the dataset records as a matching record if the score is above a previous highest score;

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tuning a Fellegi-Sunter algorithm parameter with the data  
from the entered record and data from the one of the  
dataset records; and

when the dataset records have been checked, returning the  
matching record. 5

**12.** The method of claim **11** wherein the dataset record is  
a payment record.

**13.** The method of claim **12** further comprising enriching  
at least one payment record by supplementing data in the at  
least one payment record with the customer data from the 10  
dataset.

**14.** The method of claim **11** wherein the dataset record is  
an invoice record.

**15.** The method of claim **14** further comprising enriching  
at least one invoice record by supplementing data in the at 15  
least one invoice record with the customer data from the  
dataset.

**16.** The method of claim **11** wherein the entered record is  
related to a payment.

**17.** The method of claim **11** wherein the entered record is 20  
related to an invoice.

**18.** The method of claim **11** wherein the threshold is zero.

**19.** The method of claim **11** wherein the Fellegi-Sunter  
algorithm parameter is a probability  $m$  that an amount field  
in the entered record matches an amount field in the dataset 25  
record.

**20.** The method of claim **11** wherein the Fellegi-Sunter  
algorithm parameter is a probability  $n$  that a customer  
address field in the entered record does not match a customer  
address field in the dataset record. 30

\* \* \* \* \*